Robust design of spacecraft structures under lack of knowledge

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ROBUST DESIGN OF SPACECRAFT STRUCTURES UNDER LACK OF KNOWLEDGE

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ABSTRACT

In robust design, lacks of knowledge are rarely taken into account explicitly, but this is the case in the RRDO-IG. This paper summarises the ongoing developments and perspectives for the use of the RRDO-IG methodology in a spatial industrial context, where non-linearities have to be treated. After shortly describing the RRDO-IG methodology and the actual encountered problems, we will construct an improvement strategy based on a state of the art in metamodelisation and failure probability computation.

1 INTRODUCTION

Methods for the robust design of mechanical systems have for objective to reduce the variability in system performance with respect to uncertainties in the material and geometrical properties of a mechanical structure as well as in the environmental loads. Two types of uncertainty are encountered in practice, namely random and epistemic uncertainties. Beside random ones, epistemic uncertainties are due to a lack of accurate knowledge concerning the physical laws governing the behaviour of a component or interface and can generally be reduced with more detailed modelling or experimental investigations. Epistemic uncertainties are difficult to characterize and as such are rarely taken into account explicitly in reliability analysis.

2 RRDO-IG METHOD

The RRDO-IG [1] approach is an extension of the RBDO one. It permits to design robustly a structure in regard with the lack of knowledge.

2.1 Formulation

A RRDO-IG optimization problem can be posed as follow:

$$\begin{cases} \min\limits_{\boldsymbol{d}\in R^{n_d}} f(\boldsymbol{d}) \\ with \\ \boldsymbol{m} \in U\left(\alpha, \boldsymbol{m}^{(0)}\right), \\ \alpha = \alpha_i, \\ \boldsymbol{d}_{min} \leq \boldsymbol{d} \leq \boldsymbol{d}_{max} \\ P_f(\boldsymbol{q}) \leq P_c. \end{cases} \tag{1}$$

Where:

- f is one or more cost function to optimize,
- $\boldsymbol{d}$ is the design parameters vector,
- $\boldsymbol{m}$ is the unknown parameters vector,
- $\boldsymbol{m}^{(0)}$ is the nominal value of $\boldsymbol{m}$,
- $\boldsymbol{q}$ is the concatenation of $\boldsymbol{d}$ and $\boldsymbol{m}$,
- $P_f(\boldsymbol{q})$ is the failure probability,
- P_c is the critical threshold failure probability,
- α is the horizon of uncertainty.

The first condition contains the lack of knowledge modelisation, here an info-gap method [4].
We can notice that, if $\alpha = 0$ (i.e. if no lack of knowledge) the problem becomes a simple RBDO one.

2.2 Results and perspectives

Previous works permitted to validate the RRDO-IG methodology [1], but various problems have appeared:

- Two different metamodels with comparable accuracy can give different robustness curves.
- Implemented failure probability computation method (i.e. FORM) does not always converge.

3 PROPOSED APPROACH

3.1 Improve the limit state approximation

3.1.1 Current problems

Metamodels currently used can only treat smooth functions because of their certain stiffness [1-2-7]. Indeed, in each case, the method consists in approximating the limit state globally on the entire design domain with continuous functions.
Even if it is possible to soft a metamodel increasing his functions degree, it is necessary to sample more and more the design domain to avoid bad generalization, although this action increases significantly the computation time.

3.1.2 Propositions

To avoid these problems, various methods of adaptive metamodelisation are proposed in the literature. The main idea is here to lead the sampling in accordance with the complexity of the explored area whereas currently, the sampling is done blindly before the metamodelisation.
This kind of method would permit to significantly reduce the sampling number.
As an instance, we will test an adaptive kriging method proposed by V. Dubourg [7] and an adaptive stochastic collocation method proposed by N. Agarwal [6] which can absorb non-linearities and discontinuities.

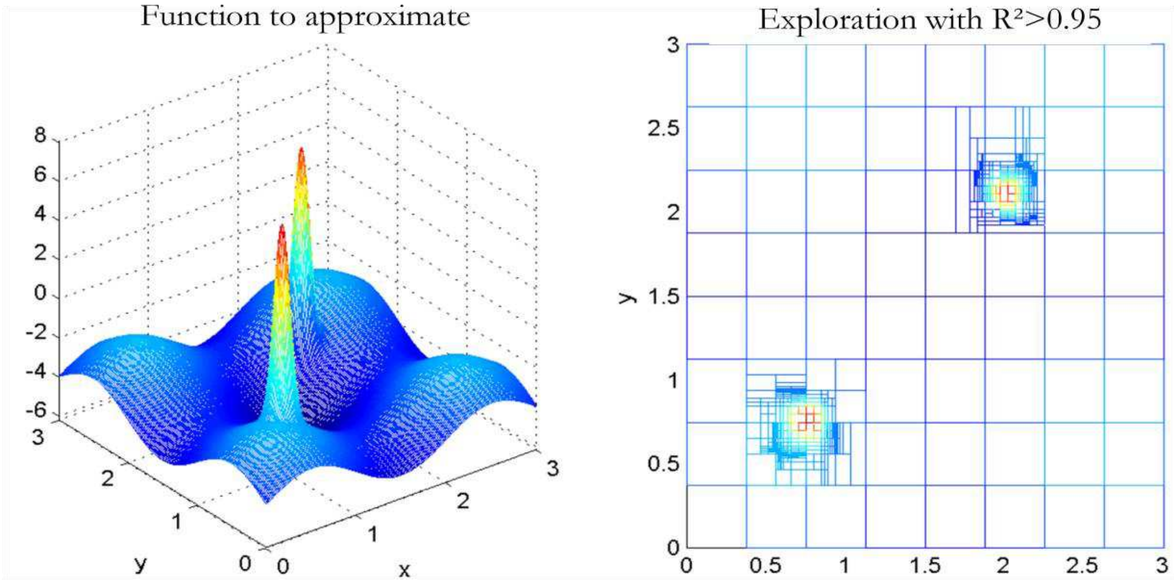

Figure 1. Design space exploration with a based
N. Agarwal's method. The refinement occurs only in highly non-linear areas.

3.1.3 Expectations

The aim of the proposed study is to determine the usage domain for each kind of metamodel regarding the type of limit state to approximate.
To attest the metamodels efficiency, generic comparison criteria will be used as R^2, ERAM, MERA [1] criteria and the number of sampling.

3.2 Compute accurately the failure probability

Previews studies show that the use of FORM method leads to important errors in the failure probability estimation in case of non-linear limit state. We propose here to test a priori more efficient methods.

3.2.1 Replace FORM by SORM

The SORM method is the extension of the FORM one to the second degree. It means that we can expect amelioration in the failure probability estimation, but it requires computing the curvatures in each dimension at the design point. On top of this, a priori, this method only permits to estimate exactly limit state until the degree two. Above, an error still occurs.

3.2.2 Test exact methods

To avoid FORM and SORM disadvantages, it would be interesting to also test exact methods like RGMR [5] which permits to exploit to the maximum the geometry of the standard space.
This kind of methods does not require finding the design point and can be optimized if quadrature points are cleverly chosen.

4 CONCLUSION

Exploring Adaptive metamodelisation methods and complex failure probability computation methods, we will try to develop the RRDO-IG methodology for an industrial use. The aim is to finally treat optimization problems with complex limit state due to non-linearities which are legion in the spatial field [3].

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